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Nature-based outdoor recreation trips: Duration, travel mode and location

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ABSTRACT

This paper studies the allocation of time to outdoor recreation trips in various natural environment types. We merge a multiple discrete-continuous demand system for time allocation with a discrete choice model for destination and travel mode choice. Accessibility enters the time allocation model through the logsum of the travel mode/destination choice stage.

The model is estimated on data for the Netherlands, which was gathered through an activity diary approach that covers one entire year. Our model shows that personal characteristics, household characteristics, contextual variables and accessibility all augment the allocation of time to the set of natural environment types. The resulting estimates allow us to evaluate outdoor recreation policy initiatives, and we simulate the impact of changes in the availability of natural environment types with a constrained optimization approach. We show that time allocation changes are rather small with our simulated policy initiative, but have the intended effect on the group of consumers which the policy initiative aims for.

1. Introduction

This paper constructs and estimates a model for time spent on dissimilar natural environment types for the enjoyment of outdoor recreation. Following Bhat et al. (2006, 2009) and Eluru et al. (2010), our model integrates the multiple discrete-continuous approach for time allocation of Bhat (2005, 2008), often referred to as the multiple discrete-continuous extreme value (MDCEV) approach, with a model of travel mode and destination choice using the GEV framework of McFadden (1978). The result is a structural model of recreational behavior that can be used to investigate the impact of policy measures with respect to recreational land use. We estimate the model in two steps: the first step is a discrete choice model for travel mode and destination choice, and afterwards we use the implied logsum value as an explanatory variable in the time allocation model which is the second step.

The model we develop offers the possibility to study several important dimensions of outdoor recreation – amount of time spent, travel mode and destination choice – in a consistent framework in which actors maximize utility. The MDCEV framework has been used to investigate the somewhat related topic of time spent on vacation by Van Nostrand et al. (2013) and LaMondia et al. (2008), but these studies do not consider travel mode and destination choice simultaneously.

We model travel mode and destination choice for outdoor recreational activities by means of a conventional discrete choice model. We substitute the results in Bhat's (2005, 2008) MDCEV model which explains participation in as well as duration of (i.e. time spent on) the activities which offers a richer picture of recreation behavior. We use a two stage (sequential) estimation procedure.

The big advantage of being able to study the duration of leisure activities in the context of a structural model comes at a cost.

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Many specifications of the MCDEV model, including the one presented here, impose an explicit constraint on the time budget, but not on the monetary budget. This implies a significant difference with many studies – notably those belonging to the economic literature - that derive behavioral equations from the maximization of utility under a monetary budget constraint and additional inequality constraints (hence also using a Kuhn-Tucker framework) but without an explicit time constraint, see for example Bhattacharjee et al. (2009), Fezzi et al. (2014). Bhat (2008) provides an elaborate comparison of the MCDEV model and the micro-economic approach.

Our study focuses on trips to natural environments for recreation purposes in the Netherlands. We make use of a database on recreational behavior of a sample of Dutch households, the Continuous Free Time Survey. The Dutch tend to agglomerate in the lower, water-abundant western parts of the country, with forty-five per cent of the inhabitants residing in crescent-shaped conurbation Randstad Holland on approximately twenty per cent of the country's surface. Randstad Holland includes major cities Amsterdam, Rotterdam, The Hague, and Utrecht, and can be compared to the San Francisco Bay Area in terms of magnitude and density.

Our results indicate that both accessibility and socio-demographics are important determinants of the variation in time allocation to outdoor recreation, in each of the natural environment types. Age, household composition, responsibilities in work and schooling, and weather situation all play an important role in the time allocation process, while accessibility seems to have the largest impact on time allocation to urban park recreation. We also reflect on the effect of some real-life policy initiative with the help of a constrained optimization approach, and our policy simulation exercise shows that an increase in supply around the thirty-eight largest cities of the Netherlands leads to a decrease in time allocated to the numéraire time-use category, and an even larger increase towards the natural environment type for which supply was increased.

The structure of the paper is as follows. Section 2 discusses the model. Section 3 continues with an examination of the data and variable specification, while Section 4 presents the estimation results of this application. Section 5 discusses our policy simulation, while Section 6 concludes.

2. The model

2.1. Utility

Our model combines the Kuhn-Tucker demand system for time-use, the MDCEV-model, of Bhat (2005, 2008) with a GEV discrete choice model (see McFadden, 1978) for characteristics of the activities on which time is spent. In this we follow Bhat et al. (2006, 2009) and Eluru et al. (2010), who use MNL. Here we offer a slight generalization by allowing the discrete choice model to be any member of the GEV family. We derive the utility function of each outdoor recreation activity as the maximum utility implied by a GEV model of transport mode and destination choice, which is a random variable. As in the publications on MDCEV models referred to above, we consider a consumer who allocates a given amount of time on activities $k = 1\cdots K$. Total utility is the sum of all sub-utilities associated with these activities:

$$U = u_1(x_1) + u_2(x_2) + \sum_{k=3}^{K} u_k(x_k, d_k, m_k) \tag{1}$$

Utility is the sum of sub-utility functions referring to each of these activities. Each time-use category is consumed in nonnegative quantities ($x_k \geq 0$, $k = 1\cdots K$). The first category serves as a *numéraire*, for which each consumer has strictly positive consumption. In our application this is basically all time not spent on recreation. The second category involves time spent on other, that is non-outdoor, recreational activities. The remaining categories capture time devoted to nature-based outdoor recreation, which are the focus of the present study. Each activity in this group represents outdoor recreation in a distinct natural environment type. For such trips the consumer has to choose a destination (d_k) and travel mode (m_k) from a set of D destination alternatives for every natural environment type and M travel modes. The total number of choice alternatives for outdoor recreation thus equals at most $Z \times D \times M$, where Z is the set of outdoor recreation environment types.[1]

All outdoor recreation trips in our model are home-based. This implies that travel mode and destination can be chosen without having to take into account the possible restrictions imposed by the mode chosen in the previous trip and that the distance between the respondent's residential location and the trip destination is always the relevant one.[2] As a consequence, we can ignore trip-chaining and consider the optimal choice of travel mode and destination for each outdoor recreation trip separately, provided that we condition on the time spent during that trip. For $k > 2$, let $u_k(x_k)$ denote the value of $u_k(x_k, d_k, m_k)$ that will be reached if destination and travel mode are optimally chosen:

$$u_k(x_k) = \max_{d_k \in D_k, m \in M} u_k(x_k, d_k, m_k) \tag{2}$$

This maximization can be interpreted as the lower part of a two-stage decision process in which the consumer first determines the optimal amount of time for each trip and subsequently decides on travel mode and destination choice for each activity to which a positive amount of time is allocated.

1 As the time unit over which consumers allocate time is exactly one day, we impose the reasonable restriction that choice for some natural environment type involves only one destination and travel mode per day.

2 Although this assumption may not always be realistic, we expect it to be so in the large majority of cases.

The first (upper) stage of the decision process is the minimization of the overall utility function U in which the optimal subutilities for outdoor recreation are substituted:

$$U = \sum_{k=1}^{K} u_k(x_k), \tag{3}$$

with respect to the time constraint:

$$\sum_{k=1}^{K} x_k = X \tag{4}$$

and non-negativity constraints:

$$x_1 > 0,\ x_k \geq 0,\ k = 2\cdots K \tag{5}$$

We will now consider both stages in greater detail.

2.2. Mode and destination choice for outdoor recreation

We specify the natural logarithm of the utility u_k as the sum of a deterministic and a random part:

$$\ln u_k(x_k, d_k, m_k) = w(x_k, d_k, m_k) + \varepsilon_{kdm},\ d = 1\cdots D_k,\ m = 1\cdots M \tag{6}$$

where $w(.)$ is the deterministic part of utility that will be specified further later on, and ε_{kdm} is the stochastic part.

The ε_{ij}'s are assumed to be GEV type I, or Gumbel, distributed, which implies that the probability that destination d and mode m are chosen when undertaking outdoor recreation at natural environment type k is equal to (see McFadden, 1978):

$$\Pr(d = d', m = m'|k) = \frac{e^{w_{kdm}} \frac{\partial G_k}{\partial exp(w_{kdm})}}{G_k(exp(w_{k11})\cdots exp(w_{kD_kM}))} \tag{7}$$

where w_{kdm} is shorthand notation for $w(x_k, d_k, m_k)$ and G is the generator function (see McFadden, 1978). Using well-known results we can write the maximum utility associated with outdoor recreation activity k as:

$$\ln u_k(x_k) = \ln G_k(exp(w_{k11})\cdots exp(w_{kD_kM})) + \varphi_k \tag{8}$$

where φ_k is a stochastic term that is Gumbel distributed with location parameter 0. The deterministic part of the right-hand side of (8) is the 'logsum' or inclusive value which – in the context of trip choice analysis – can be interpreted as an accessibility measure.[3]

2.3. Time allocation

We will now consider the time allocation stage. Using (8), we can rewrite (4) as:

$$U = u_1(x_1) + u_2(x_2) + \sum_{k=3}^{K} G_k(exp(w_{k11})\cdots exp(w_{kD_kM}))e^{\varphi_k} \tag{9}$$

where it should be understood that every w_{kdm} is a function of x_k. Maximization of (9) under the constraints (4) and (5) gives the optimal time use of the consumer. The accessibility to various natural environment types for the consumer is indicated by the 'logsum' terms. The model thus allows us to study how differences in accessibility affect the time spent by the consumer on various environment types for the purpose of outdoor recreation.

It should be observed that the formulation of (9) also allows for the possibility that some determinants of the utility associated with the recreational trip have no impact on travel mode choice.[4] To see this, consider the additive specification:

$$w_{kdm} = w_k^1(q_k, x_k) + w_{kdm}^2(v_{kdm}, x_k) \tag{10}$$

where q_k is a vector of characteristics of outdoor recreation type k, and v_{kdm} is a vector of characteristics of the location and/or mode that determine its attractiveness for natural environment type z. It is easy to verify that the first term – $w_k^1(q_k, x_k)$ – does not appear in the choice probabilities as defined in (7). Hence the variables q_k have no impact on destination or mode choice, although they affect the utility attached to outdoor recreation of type k. This offers substantial flexibility in formulating a specific model.

The model just derived becomes Bhat's (2005, 2008) MDCEV model for time allocation if we specify the function w_{kdm} as:

[3] See, for instance, Walker and Ben-Akiva (2011), Ben-Akiva and Bierlaire (1999), De Palma et al. (2006).

[4] To see this, consider the additive specification , where is a vector of characteristics of outdoor recreation type , and is a vector of characteristics of the location and/or mode that determine its attractiveness for natural environment type . Because of the homogeneity of degree one of the function , the first term – – does not appear in the choice probabilities as defined in (7). Hence the variables have no impact on destination or mode choice, although they affect the utility attached to outdoor recreation of type . See (12).

$$w_{kdm} = \left[\beta_k q_k + \ln\left(\left(\frac{x_k}{\gamma_k}+1\right)^{\alpha_z} - 1\right) + \ln\left(\frac{\gamma_k}{\alpha_k}\right)\right] + [\delta_k v_{kdm}] \tag{11}$$

In this equation the square brackets indicate, respectively, the functions w_k^1 and w_{kdm}^2. The Greek letters denote vectors of parameters that have to be estimated. Substitution of (11) into (9) gives:

$$U = u_1(x_1) + u_2(x_2) + \sum_{k=3}^{K} \frac{\gamma_k}{\alpha_k}\left(\left(\frac{x_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right) e^{\beta_k q_k + \ln G_k(exp(\delta_1 v_{k11})\cdots exp(\delta_k v_{kD_kM})) + \varphi_k} \tag{12}$$

as in Bhat et al. (2006, 2009) and Eluru et al. (2010). Eq. (12) is the utility function of Bhat (2008) with a logsum term $\ln G_k(exp(\delta_1 v_{k11})\cdots exp(\delta_k v_{kD_kM}))$added to the vector of characteristics.[5] It is easily verified that this new term does not change the properties of the model as it plays the same role as the elements of $q$with a coefficient set equal to 1.

It should be noted that the time spent on activity k, x_k, does not appear in the w_{kdm}^2 as it has been specified in (11). The reason is that we assume that time spent on outdoor recreation at natural environment type k does not affect destination or travel mode choice. We make this simplifying assumption because the introduction of a relationship between time spent on an activity on the one hand and the choice of travel mode and destination on the other would complicate the model substantially.[6]

2.4. Further specification issues

In our application, reported below, two specifications of $G(.)$ have been used. The first one is:

$$G_k(exp(w_{k11})\cdots exp(w_{kD_kM})) = \left(\sum_d \sum_m exp(w_{kdm})^{1/\rho_k}\right)^{\rho_k} \tag{13}$$

The second is a nested logit formulation. For instance, if the nests refer to the destination, then we have:

$$G_k(exp(w_{k11})\cdots exp(w_{kD_kM})) = \left(\sum_d \left(\sum_m exp(w_{kdm})^{1/\rho_d}\right)^{\rho_d/\rho_k}\right)^{\rho_k} \tag{14}$$

If we use (17) the probability function for travel mode and destination choice is multinomial logit:

$$\Pr(d = d^{'}, m = m'|k) = \frac{e^{\delta_k v_{kd'm'}/\rho_k}}{\sum_d \sum_m e^{\delta_k v_{kdm}/\rho_k}} \tag{15}$$

Note that the coefficients δ_k and ρ_k are not separately identified in the destination/travel mode choice model; only their ratio can be estimated. However, the coefficient ρ_k can be estimated in the time-use model. To see this, use (16) to write:

$$U = u_1(x_1) + u_2(x_2) + \sum_{k=3}^{K} \frac{\gamma_k}{\alpha_k}\left(\left(\frac{x_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right) e^{\beta_k q_k + \rho_k \ln(G^*) + \varphi_k} \tag{16}$$

with $G^* = \sum_d (\sum_m exp(\delta_k v_{kdm})^{1/\rho_d})^{\rho_d/\rho_k}$ if the nested logit specification is used and $G^* = \sum_d \sum_m exp(\delta_k v_{kdm})^{1/\rho_k}$ if the multinomial logit it used.

To complete our discussion of the specification of the model, we have to consider the first two time-use categories. The utility function that will be used for time-use category "other recreation" ($u_2(x_2)$) is nearly identical to that of the outdoor recreation categories. The only difference is that we do not include an accessibility indicator (through destination and travel mode choice) for this time-use category, and thus the G function misses out. The *numéraire* time-use category does not have a separate translation parameter, since we assume strictly positive allocation for this commodity. The final utility function becomes:

$$U = \frac{1}{\alpha_1} x_1 e^{\varphi_1} + \frac{\gamma_2}{\alpha_2}\left(\left(\frac{x_2}{\gamma_2}+1\right)^{\alpha_2} - 1\right) e^{\beta_2 q_2 + \varphi_2} + \sum_{k=3}^{K} \frac{\gamma_k}{\alpha_k}\left(\left(\frac{x_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right) e^{\beta_k q_k + \rho_k \ln G_k^* + \varphi_k} \tag{17}$$

Maximization of (17) with respect to x_k, $k = 1\cdots K$ subject to the time budget constraint (4) and the non-negativity restrictions leads to a closed-form expression for the probability that a particular time allocation will be observed (see Bhat, 2005, 2008).

2.5. Discussion

Recreation studies have frequently focused on specific recreation attractions. The value of forests for outdoor recreation has been studied by for example Willis and Garrod (1991), Bestard and Font (2010), and Bartczak et al. (2011), while Goossen and Langers (2000), Fleischer and Tsur (2009), and Pouta and Ovaskainen (2006) focus on the potential of agricultural land, and Scott and Munson (1994) study park land use. However, there are good reasons to believe that substitution is important. One of the merits of a

[5] Note that only the second part of the function () appear in the generator function in (12). This is related to the fact that the first part (does not appear in the choice probabilities as discussed in the previous footnote.

[6] See McConnell (1992) and Larson and Lew (2005) for analyses of the relationship between travel time (an important aspect of destination choice) and time spent at a destination.

model such as in Bhat et al. (2006), Eluru et al. (2010) and the model used in this paper is that it allows to paint a fuller picture of recreational behavior. Here, time use, travel mode choice, and destination choice are integrated in one framework for the whole set of outdoor recreational activities.

3. Model specification

3.1. Recreation preference data

This paper uses data obtained from Dutch market research agency TNS-NIPO. Their Continuous Free Time Survey (CVTO) is a two-yearly online survey, covering a representative sample of Dutch households. Each week a set of respondents is inquired to register choices made for recreation during that week, and we apply the survey held between April 2006 and March 2007.

The survey instructs respondents to register trips whenever the respondent participates in some activity outside the own residence, with the activity lasting at least sixty minutes (including travel time), and with the own residence as start and end point of the trip.[7] The database is not constrained to nature-based outdoor recreation, but this activity type comprises twenty-one per cent of the total number of trips and is the most popular category of recreation activities in the database.

The sample used in this paper has been obtained after deleting the respondents who have not reported their household income, which is true for 3437 respondents and thus around 20% of the respondents. As noted in the model section, we assume a time budget of exactly one day per choice occasion. Since the survey asks each respondent to register trip details for exactly one week, each respondent contributes seven cases to our sample.[8] With the aforementioned restrictions our sample consists of 12,955 respondents, and thus 90,685 time allocation observations. The destination-mode choice models consist of 7662 unique trips for nature-based outdoor recreation. This set of trips is at the basis of each destination-mode choice model, as well as the time allocation model.

3.2. Dependent and independent variable specification

For each trip the respondent lists the type of environment and the municipality which has served as destination. The original environment type choice set has twelve alternatives, yet we have decided to categorize these alternatives into four groups of natural environments. The primary reason are the similarities between some of the environment types and the spatial vicinity of some of the environments to each other. Recreation on riverbeds is not exactly equal to recreation on a beach, but the two are probably close substitutes. Since dunes are close to the sea, it is difficult to distinguish between recreation on the beach and in the dunes. That's why all environment types related to water have been grouped into one category. Forestland, heath land, and drifting sands have also been grouped together because heath and drifting sands are in the Netherlands in most – if not all – cases surrounded partly or completely by forests. In the end, we get these four categories:

water space and coastal dune land recreation (*e.g.,* trips to the beach, to lakes, to coastal dunes, at recreational waters, and at rivers);
forestland, heath land, and drifting sands recreation;
agricultural land recreation;
urban park recreation.

Reported duration time for outdoor recreational trips serves as the dependent variable for each time-use category. Since there is no restriction of maximally one "other recreation" trip, destination and travel mode per day, we aggregate duration times for this time-use category whenever the respondent reports more than one trip per day. We arrive at the value for the "other time" time-use category by subtracting the values of all recreation time-use categories from the total number of minutes per day. In addition to trip duration and natural environment type, the respondent also registers travel mode for each trip. We consider three mode types in the destination-mode choice model: motorized travel, bicycle travel, and pedestrian travel.[9]

Destination choice is not only at the level of environment type, but also at the level of the municipality. The consumer thus chooses an environment type and a municipality. The number of alternatives in the municipality choice set hinges on the number of municipalities having some natural environment type within municipality borders.[10] Maximum size of the choice set therefore equals the number of municipalities($d = \{1, 2, \cdots, 458\}$). We determine availability in each municipality with the use of publicly available data of Statistics Netherlands. Since 1979 Statistics Netherlands has been updating land-use statistics regularly, and we apply data of 2006. The extent of supply is also included as explanatory variable in each destination-mode choice model, and this extent is determined by aggregating the size of all individual patches per natural environment type within municipality borders. All

[7] Thus, respondents do not state how much time they spend on in-home recreational activities (*e.g.*, using ICT or watching television. The *numéraire* time-use category however automatically accommodates time allocation to these activities into the Kuhn-Tucker demand system.

[8] Although this may imply we are dealing with a panel structure here, we actually consider the seven cases of each respondent individually. Introducing random or fixed individual effects in this model as a potentially useful extension.

[9] For motorized travel, we choose to ignore the distinction between automobile travel, motorcycle travel, and public transport, as the latter two modes of transport are revealed, altogether, in not more than two per cent of the cases.

[10] We apply the same definitions as Statistics Netherlands, who set a lower limit of one hectare for each natural environment type.

Table 1
Explanatory variable definitions and summary statistics.

Variable	Description	Summary	Min.	Max.
MDCEV time allocation model				
q_{male}	Respondent is male (0/1)	0.502	0	1
$q_{age0-15}$	Respondent has age of at most 15 (0/1)	0.168	0	1
$q_{age16-25}$	Respondent has age of at least 16 and at most 25 (0/1)	0.105	0	1
$q_{age26-45}$	Respondent has age of at least 26 and at most 45 (0/1)	0.324	0	1
q_{age65+}	Respondent has age of at least 65 (0/1)	0.144	0	1
$q_{nonnative}$	Respondent has non-native ethnic background (0/1)	0.096	0	1
q_{temp}	Avg. temperature at the day of observation (divided by 10)	1.216 (0.57)	−0.190	2.690
q_{precip}	Total precipitation at the day of observation (divided by 10)	0.239 (0.44)	0	2.520
$q_{hhincome}$	Monthly per person household income (divided by 1000)	1.418 (1.05)	0.017	12.500
q_{single}	Respondent is a single-person household (0/1)	0.128	0	1
$q_{children}$	Respondent is in a household with children aged below twelve (0/1)	0.369	0	1
$q_{fulltime}$	Respondent works 36 or more hours per week (0/1)	0.274	0	1
$q_{parttime}$	Respondent works less than 36 h per week (0/1)	0.210	0	1
$q_{missing}$	Respondent has not registered work status (0/1)	0.127	0	1
$q_{weekend}$	Day of observation is Saturday or Sunday (0/1)	0.286	0	1
Destination-mode choice models				
$c_{waterloc}$	Municipality is sea, arm of the sea, and/or IJsselmeer location (0/1)	0.25	0	1
c_{dunes}	Municipal coastal dune land size (in ha.)	71.81 (365.64)	0	3414
$c_{recwater}$	Municipal recreational water (in da.)	21.19 (43.35)	0	445
c_{forest}	Municipal forestland, heath land, and drifting sands (in ha.)	851.52 (1681.45)	0	19,401
$c_{agriculture}$	Municipal agricultural land (in ha.)	4990.83 (5221.4)	7	40,909
c_{park}	Municipal park land (in ha.)	60.51 (123.31)	0	1392

Note: (0/1) indicates a categorical variable. Summary statistics for the set of MDCEV time allocation model variables are means (standard deviations) over the 12,955 respondents. Summary statistics for the destination-mode choice variables are means (standard deviations) over the set of destination alternatives.

municipalities have agricultural land within municipality borders, but the other types are not available for recreation in every municipality. There is recreational water and/or coastal dunes in 393 municipalities, urban park land in 432 municipalities, and forest- and/or heathland in 449 municipalities.

Travel distance towards the reported municipality is taken from the database. Travel distance towards the non-chosen municipalities is computed via a procedure explained in Appendix A. Last, the survey database includes detailed information about individual and household socio-demographic characteristics. This set of explanatory variables will be added to the MDCEV time allocation model, and captures the generic and contextual differences in preference across individuals. We include individual characteristics such as age, gender, ancestry, and number of hours per week spent on work and/or schooling. Our set of household characteristics consists of monthly per person household income and the presence of children aged twelve years or younger in the household. Weekend day and weather situation variables are added as contextual characteristics. The weather situation variables are publicly available and taken from the website of the Royal Netherlands Meteorological Institute. Table 1 lists sample statistics and variable definitions.

4. Estimation procedure

We estimate the model in two steps. We start with estimating the destination and mode choice decisions (4.1) and use the results in estimating the MDCEV model (4.2).

4.1. Destination-mode choice stage

We estimate distinct destination-mode choice models for each natural environment type. This stage thus does not consider consumer preferences *across* the set of distinct natural environment types, but only what drives consumers to choose for some destination and travel mode conditional upon the choice of some environment type in trips with a nature-based outdoor recreation purpose. In section 2 we discussed that the choice probabilities depend only on the w_{kdm}^2's which we specified there as a linear function $\delta_k v_{kdm}$of the characteristics. We now specify this function further as:

$$w_{dm}^2 = \omega_m + \beta c_d + \phi_m h_{distance} + \psi_m (h_{distance} r) \tag{18}$$

Since all terms in this utility function refer to a specific type of outdoor recreation, we have suppressed the suffix k. The coefficient ω_m is a mode-specific constant term, β is a vector of generic coefficients for a vector of environment type-specific characteristics (c_d), ϕ_m is a mode-specific coefficient for travel distance (h), and ψ_m is a vector of mode-specific coefficients for the interaction effect between travel distance and a vector of individual, household, and contextual characteristics (r). We have tested various transformations of both travel distance and supply of natural environment, and have included the natural logarithm for both the supply of natural environment and travel distance. For each environment type model the probability function is, as in Train (2009):

$$P_{kdm} = \frac{exp(w_{dm}^2/\sigma)\left(\sum_{\{d,m\}\in B_j} exp(w_{dm}^2/\sigma)\right)^{\sigma-1}}{\sum_{j'=1}^{J}\left(\sum_{\{d,m\}\in B_{j'}} exp(w_{dm}^2/\sigma)\right)^{\sigma}} \tag{19}$$

In this equation j refers to the nests, and J is the total number of nests. Thus, at the branch level we model destination choice, while each alternative at the leaf level of the decision tree is a mode alternative. We test both multinomial logit (MNL) and nested logit (NL), to check for correlation in unobserved factors between alternatives. The probability function is the same for these two logit structures, except in the estimation of parameter σ. This parameter equals one for MNL models, while we constrain σ to one generic estimated coefficient for all mode nests in the NL models.

Estimation of the nested logit models resulted in values of σ that were in all cases larger than 1, and therefore not necessarily consistent with utility maximization.[11] We therefore concentrate on MNL for travel mode and destination choice here. The estimates for each natural environment type are presented in Table 2. The coefficients are generally in line with our expectations. Travel distance works as a disutility to the consumer: destinations become less attractive to the consumer when the required distance to travel increases. Logically, the absolute value of travel distance coefficients increases the slower a mode of travel is. We expected the coefficients for recreation at water spaces and coastal dune land to be smallest in absolute terms, as the most attractive alternatives of this environment type are often located on the fringes of the country. If chosen, the required distance to travel is thus also higher.

The coefficient of each environment type size variable is statistically significant at the 1% level. The sign of the coefficients confirms our initial expectations that environment type size matters for consumers in their decision on which destination to visit for outdoor recreation. The interaction effects between travel distance ($h_{distance}$) and the set of characteristics often yield significant coefficients, and, for example, show that consumers of nonnative descent tend to be more averse to travel for outdoor recreation than consumers with Dutch native backgrounds, except in the case of water space and dune land recreation. Resistance against travelling long distances is lower in the weekend, although the effect is only significant for motorized travel. Contrary to our belief, low-income consumers are not always more averse to travel by car or other motorized travel than consumers with higher incomes.

The coefficients of each destination-mode choice model can be translated graphically, which yields indicators for accessibility. The denominator of probability function (19) describes the attractiveness of the choice set for each type of consumer, at each possible location. Of course, we require some assumptions on individual, household and contextual characteristics, but if taken the accessibility heat maps of environment types “Forestland, heath land, and drifting sands” and “Urban park recreation” are as shown in Appendix B.[12] On top of the heat map we have projected all unique patches of the environment type, and the similarities of this projection with our heat map imply that our model has yielded estimates that correspond pretty well with the spatial distribution of environment types across the Netherlands. Consumers in Randstad Holland (in the west of the Netherlands) are relatively well-endowed with alternatives for urban park recreation, yet rather minimally with respect to opportunities for recreation at forests or heath land.

4.2. The MDCEV time allocation model

A commonly encountered difficulty associated with the MDCEV model is that the empirical identification of (17) is not straightforward, as the satiation and translation parameter tend to capture the same effect. Bhat (2008) proposes to estimate either α or γ, and constrain the other, which still leads to similar estimation profiles. We adopt this strategy and estimate the utility function with α, constraining γ for all interior time-use categories to one. Table 3 reports the estimates of this procedure, with, equivalent to standard discrete choice models, one alternative in the choice set serving as base category, to which all other parameters are scaled. Here the *numéraire* time-use category serves as base category, and thus all its parameters are equal to zero with utility being the exponential of zero. Standard errors have been computed treating the inclusive value from the transport mode/destination stage as known.[13]

The alpha parameters capture satiation effects in the execution of outdoor recreation and other recreation: these parameters reduce marginal utility with increasing consumption. All estimated coefficients are within the range of 0.8 and 0.9, which are fairly low satiation values (Bhat, 2008). The values of these coefficients intuitively imply that once a consumer decides to start either an outdoor recreation trip in some environment type or another recreation trip there is not much incentive to change the type of activity or environment. Thus, the low alpha parameter values imply that consumers are not expected to allocate time to all outdoor time-use categories, which naturally progresses from our setup to restrain each choice occasion to twenty-four hours. The alpha values of the separate time-use categories are comparable, but the one for outdoor recreation at environment type “water space and coastal dune

[11] The estimates of the NL model are available at request with the authors.

[12] Our representative consumer is female, of western ancestry, has no young children in the household, has a household income not belonging to the lowest twenty percent, and recreates outdoors on Saturday or Sunday. We assume for each municipality that the consumer resides in the postal code area which also hosts city hall.

[13] In fact, it is a random variable, due to the fact that it contains estimated parameters. The effect of ignoring this issue is that standard errors of the MDCEV model may be biased downwards.

Table 2
MNL estimates destination-travel mode choice models.

	Water space and coastal dune land recreation		Forestland, heath land and drifting sands recreation		Agricultural land recreation		Urban park recreation	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
$c_{waterloc}$	0.279^{***}	0.018	–	–	–	–	–	–
c_{dunes}	0.210^{***}	0.013	–	–	–	–	–	–
$c_{recwater}$	0.796^{***}	0.075	–	–	–	–	–	–
c_{forest}	–	–	0.797^{***}	0.019	–	–	–	–
$c_{agriculture}$	–	–	–	–	0.527^{***}	0.036	–	–
c_{park}	–	–	–	–	–	–	1.044^{***}	0.034
Motorized travel								
$h_{distance}$	-1.506^{***}	0.028	-1.751^{***}	0.033	-1.651^{***}	0.050	-1.566^{***}	0.055
$h_{distance} \times r_{male}$	-0.019	0.026	0.154^{***}	0.031	0.162^{***}	0.050	0.068	0.055
$h_{distance} \times r_{nonnative}$	0.163^{***}	0.046	-0.053	0.049	-0.105	0.091	-0.488^{***}	0.117
$h_{distance} \times r_{children}$	-0.117^{**}	0.029	-0.102^{***}	0.034	-0.464^{***}	0.061	0.027	0.056
$h_{distance} \times r_{weekend}$	0.173^{***}	0.025	0.155^{****}	0.031	0.063	0.051	0.137^{**}	0.054
$h_{distance} \times r_{lowincome}$	0.166^{***}	0.032	-0.155^{***}	0.044	0.195^{***}	0.058	-0.272^{***}	0.075
$\delta_{motorized}$	0.420^{***}	0.061	-0.351^{***}	0.060	-1.141^{***}	0.088	-1.287^{***}	0.078
Bicycle travel								
$h_{distance}$	-1.708^{***}	0.051	-1.963^{***}	0.055	-1.956^{****}	0.047	-1.824^{***}	0.080
$h_{distance} \times r_{male}$	-0.099^{*}	0.058	0.194^{***}	0.056	0.278^{***}	0.052	-0.031	0.086
$h_{distance} \times r_{nonnative}$	-0.052	0.165	-0.368^{***}	0.128	-0.083	0.105	-0.471^{**}	0.202
$h_{distance} \times r_{children}$	-0.014	0.062	-0.035	0.062	-0.364^{***}	0.064	-0.005	0.090
$h_{distance} \times r_{weekend}$	0.037	0.063	0.099^{*}	0.056	0.024	0.054	0.062	0.089
$h_{distance} \times r_{lowincome}$	0.160^{**}	0.075	-0.175^{**}	0.084	0.059	0.082	-0.084	0.125
$\delta_{bicycle}$	-0.131^{*}	0.067	-0.599^{***}	0.064	0.046	0.057	-0.996^{***}	0.068
Pedestrian travel								
$h_{distance}$	-1.834^{***}	0.059	-2.059^{***}	0.053	-2.198^{***}	0.064	-1.969^{***}	0.063
$h_{distance} \times r_{male}$	-0.060	0.058	-0.076	0.061	0.279^{***}	0.073	0.088	0.072
$h_{distance} \times r_{nonnative}$	0.225^{***}	0.084	-0.373^{***}	0.125	-0.435^{***}	0.170	-0.363^{**}	0.173
$h_{distance} \times r_{children}$	-0.046	0.063	-0.098	0.066	-0.395^{***}	0.076	-0.173^{**}	0.081
$h_{distance} \times r_{weekend}$	0.076	0.060	0.094	0.061	0.054	0.073	0.044	0.073
$h_{distance} \times r_{lowincome}$	0.195^{***}	0.069	-0.149^{*}	0.078	0.297^{***}	0.095	-0.201^{*}	0.113
N	2.240		2.211		1.712		1.499	
LL(0)	−15842.23		−15931.66		−12370.02		−10743.39	
LL	−7562.09		−6381.44		−4748.05		−2650.69	

Note: statistical significance at the 10%, 5%, and 1% level is respectively denoted with **, ***, and ****.

land” is a bit higher. This implies that a trip to this environment type is least likely to be succeeded by another recreation activity or trip to another environment type. The reason could be that spending a whole day on the beach can mean the combination of a number of activities like swimming, sunbathing, taking a walk in the dunes and dining, whereas for the other types of activities the variety in the possible way of spending time seems less.

The deterministic component of the utility function (17) consists of a constant term for all interior time-use categories and a number of characteristics specific to the individual, household and context. Generally, the model yields statistically significant and plausibly signed coefficients across the set of time-use categories. The constant terms vary from -7.7 to -12.9, and the exponentials of these constants indicate that baseline marginal utility – which does not take into account characteristics of the respondent – for outdoor recreation in any type of environment and other recreation is low. The lower the exponentials of these constants, the more likely it is that consumers allocate time to other, possibly non-recreation, activities. The constant term for “Other recreation” is significantly larger than for the outdoor recreation time-use categories, which implies that consumers derive more utility from this time-use category at baseline conditions.

The coefficients for the included age categories reveal that respondents aged sixteen to twenty-five spend significantly less time on each outdoor recreation time-use category. It seems that competition of other recreational activities, put together into time-use category “Other recreation”, is the reason, as the coefficient for this time-use category is positively signed and significant. Respondents of the youngest age category also usually allocate less time to each type of environment, except for urban park recreation. This is consistent with the findings of for example Payne et al. (2002), who indicate that youngsters are the prime users of urban parks for outdoor recreation. Also Dutch surveys, such as the Big Greenery Study performed by the municipality of Amsterdam (Smeets and Gaddet, 2008), previously found that youngsters are the most frequent users of urban parks, although this study also finds such an effect for respondents aged 16–25. Our study on the other hand finds a small effect for respondents aged over sixty-five. This category of users might prefer urban parks because of the quality of recreational facilities this type of environment usually offers. In light of the current ageing of society in most Western European countries, this type of environment could become more and more

Table 3
MDCEV time allocation model.

	Forest, heath land, and drifting sands recreation		Urban park recreation		Water space and coastal dune land recreation		Agricultural land recreation		Other recreation	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
$\alpha_{satiation}$	0.859***	0.098	0.851***	0.139	0.895***	0.095	0.858***	0.124	0.820***	0.016
$q_{constant}$	−12.797***	0.137	−12.644***	0.203	−12.453***	0.121	−12.928***	0.171	−7.718***	0.031
q_{male}	−0.126***	0.053	0.034	0.061	0.311***	0.052	0.020	0.062	−0.054***	0.015
$q_{age0-15}$	−0.363***	0.109	0.513***	0.138	−0.175*	0.102	−0.180	0.125	0.254***	0.032
$q_{age16-25}$	−0.920***	0.105	−0.454***	0.122	−0.224**	0.093	−0.855***	0.124	0.280***	0.025
$q_{age26-45}$	−0.276***	0.070	−0.114	0.098	0.075	0.073	−0.216**	0.085	0.027	0.021
q_{age65+}	−0.056	0.084	0.197*	0.114	−0.200**	0.087	0.043	0.098	−0.046	0.028
$q_{nonnative}$	0.110	0.075	0.296***	0.097	−0.237***	0.087	0.012	0.096	0.143***	0.023
$q_{fulltime}$	−0.609***	0.105	−0.568***	0.135	−0.782***	0.103	−0.896***	0.128	−0.363***	0.029
$q_{parttime}$	−0.235***	0.106	−0.616***	0.142	−0.456***	0.107	−0.508***	0.132	0.175***	0.029
$q_{missing}$	0.130	0.116	0.588***	0.129	0.013	0.109	0.326**	0.124	−0.061*	0.033
$q_{hhincome}$	0.066***	0.019	−0.131***	0.035	0.059***	0.023	0.078***	0.027	0.034***	0.007
q_{single}	−0.012	0.070	0.182*	0.094	−0.249***	0.080	−0.364***	0.095	0.009	0.022
$q_{children}$	−0.185***	0.071	−0.105	0.094	−0.131*	0.069	−0.176**	0.084	−0.065***	0.020
q_{temp}	0.203***	0.039	0.199***	0.050	0.652***	0.040	0.292***	0.045	0.094***	0.011
q_{precip}	0.046	0.052	0.008	0.068	−0.180***	0.060	−0.059	0.066	0.097***	0.014
$q_{weekend}$	0.720***	0.067	0.380***	0.081	0.518***	0.071	0.306***	0.081	0.158***	0.023
$q_{weekend} \times q_{fulltime}$	0.470***	0.117	0.402***	0.158	0.471***	0.120	0.820***	0.148	0.522***	0.037
$q_{weekend} \times q_{parttime}$	0.109	0.119	0.166	0.188	0.351***	0.128	0.393**	0.155	0.163***	0.039
$q_{weekend} \times q_{missing}$	−0.129	0.137	−0.190	0.162	−0.031	0.142	0.034	0.151	0.134***	0.047
$\varrho_{inclusivevalue}$	0.271***	0.013	0.165***	0.021	0.213***	0.021	0.249***	0.017	–	–

*Note: s*tatistical significance at 10%, 5%, and 1% is denoted with *, **, and ***. Note that statistical significance for the inclusive value parameters is evaluated for a value of one. All other coefficients are related to the base category, the *numéraire* time-use category. “Female” serves as reference for “Male”, while omitted categorical variable “Age 46 to 64” is base for other age groups. Categorical variable $q_{nonnative}$ is counterpart to Dutch native descent. The household composition variables are in relation to “Household without young kids”, while “Weekday” is omitted for day of the week and “No work” for work situation.

important for the participation in outdoor recreation activities in the future.

In studies on outdoor recreation often choices of (second- or third-generation) immigrants are considered, as this group is taking an increasingly prominent role in society and knowledge on their preferences for outdoor recreation is generally limited. Table 3 shows that there is a significant effect of ethnic background on time allocation to urban parks and other recreation (being positive), while time allocated to environment type water space and coastal dune land is significantly smaller. It is worth mentioning that this agrees with evidence provided by Buijs et al. (2009) on the non-use (existence) value that Dutch consumers with non-native ethnic backgrounds attach to open space types: while native Dutch consumers value wilderness and (seemingly) uncontrolled nature highly, consumers with non-Dutch ethnic backgrounds perceive managed landscapes (urban parks being an obvious example, as also Tinsley et al., 2002 reported) as prettier scenery.

Notice that household composition also seems to have influence on time allocation. Single people and respondents of households with young children allocate less time to some environment types in comparison to the reference category, here respondents of households without young children. These findings complement those of Lee and Bhargava (2004) and Voorpostel et al. (2010), who study time-use of dissimilar types of households, and Bhat and Gossen (2004), who pay attention to the effect of household composition on the number of weekend-day trips undertaken for outdoor recreation. Here, respondents of households with young children allocate less time to outdoor recreation in forest-like environments, and more surprisingly, at water spaces or coastal dune land.

The model has also looked at the effect of the part of the week and employment situation on the amount of time allocated to any of the (outdoor) recreation types. As could be expected, consumers generally spend more time on outdoor recreation (in every type of environment) on weekend days. Other responsibilities (*e.g.* work, education) are likely to affect the consumer’s opportunities on weekdays. The interaction effect of weekend days with employment status indicates that the effect is even stronger for consumers with a fulltime job, whereas the effect is smaller or insignificant for consumers with less time allocated to work or education.

While the authorities or consumer can control many factors, they cannot control all of them, with weather conditions being an obvious example. Solid weather conditions are often seen as a prerequisite for participation in outdoor recreation (see *e.g.,* Dwyer, 1988; Tucker and Gilliland, 2007), but how the effect of weather augments time allocated across dissimilar environment types is unknown. Our estimates show that higher temperatures increase time spent on outdoor recreation in all of the natural environment types. As expected, beach recreation is a popular activity on hot summer days, as Moreno et al. (2008) have pointed out before. Strikingly, the amount of precipitation on the day of observation does not matter as much as the coefficient for each natural environment type is insignificant, except for water spaces and dune land.

Our estimates for the accessibility indicators, derived from the first stage of the model, reveal a substantial and statistically significant impact of the accessibility of outdoor recreation types on the time spent on these activities. The similar order of magnitude of the estimated coefficients indicate that the effect of accessibility is in essence comparable across all natural environment types. We expected some lower value for the inclusive value coefficient of time-use category "urban park recreation", as this environment type is distinctively different (*e.g.* in terms of naturalness) when compared to the other natural environment types, and its location is often in-between consumers' settlements. Indeed, our estimates show that the coefficient is lowest for this environment type, which reveals that its time allocation is least influenced by accessibility. This finding might reveal that the use of natural environments outside the urban confines heavily depends on supply, and policy-makers can actually affect consumers' choices for outdoor recreation with an increase in supply of some natural environment type just outside city borders.

5. Policy simulation

5.1. Policy intervention: Greater provision of recreation facilities around urban regions

As noted in section 3.1, urban regions in the Netherlands are expected to grow due to population growth and interregional migration, which might put the set of existing outdoor recreation opportunities in these regions under pressure and yield an unsatisfactory proportion of built and "green-blue" environments, also because not every natural environment type can accommodate the same number of consumers (Berkers et al., 2009).

National authorities have therefore implemented a policy program specifically focusing on recreation for urban-region consumers. This program, Recreation Around The City (usually abbreviated as RodS), aimed to reduce current and future shortages through the creation of areas with very high recreational use capacity. Nature-based outdoor recreation opportunities created according to the RodS principle should accommodate at least twenty day trips per hectare, which is a minimum that is usually only achieved at urban park land (De Vries et al., 2004).

RodS provides inspiration for policy simulation. The creation of high-quality recreation sites at the border of urban regions increases accessibility for outdoor recreation purposes, especially for those residing in urban regions, which might have an effect on time allocation. Our framework can evaluate such an increase in access through the calculation of alternative logsums. Therefore, we simulate an increase in supply of urban park land (at the cost of agricultural land) for the thirty-six major cities of the Netherlands. These cities are part of the "big cities policy" program of the national government and often have to deal with, according to Berkers et al. (2009), an overabundance of land with urban functions and a shortage of land with green or blue functions. Fig. 1 shows for

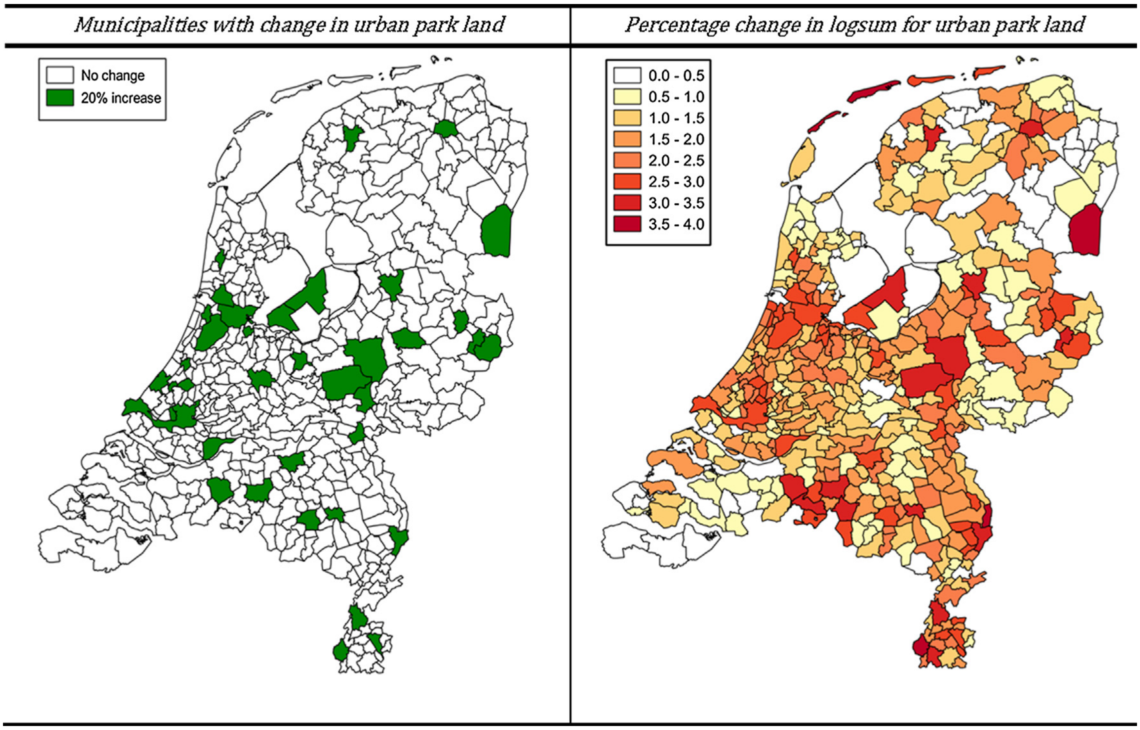

Fig. 1. Effect of policy initiative Recreation around the City.

Table 4
Effect of increase in supply of urban park land on destination choice.

	Destination		Average distance		Travel mode		
	G36	Non-G36	G36 as destination	Non-G36 as destination	Motorized	Bicycle	Pedestrian
Old situation	57.05	42.95	2.900	0.792	1.3	0	98.7
New situation	57.91	42.09	2.951	0.752	1.3	0	98.7

Note: The table lists percentages for "Destination" and for "Travel mode". "Average distance" shows the travelled distance in kilometers with either G36 cities or non-G36 towns as destination.

Table 5
Effect of increase in supply of urban park land on time allocation.

	All respondents		Respondents with change		
	Average	Std. Dev.	Average	Std. Dev.	Share of total
Other time	−0.067	0.994	−2.881	5.843	2,3%
Other recreation	−0.040	0.700	−6.451	6.097	0,6%
Forestland, heath land and drifting sands recreation	−0.000	0.060	−1.650	3.801	0,0%
Urban park land recreation	0.126	1.430	11.782	7.322	1,1%
Agricultural land recreation	−0.018	0.238	−1.316	1.586	1,3%
Water space and coastal dune land recreation	−0.001	0.090	−5.182	6.600	0,0%

Note: the change in time (minutes) allocated to each time-use category is denoted in the columns with *Average* on top. "All respondents" represents the average and standard deviation over the entire respondent set, while "Respondents with change" only considers the cases in which time allocation changes. The part of the respondent set that changes time allocation with respect to the total number of respondents is denoted in the "Share of total" column.

which municipalities we have raised supply of urban park land, with twenty per cent of the existing supply.[14]

5.2. *Policy evaluation*

This section discusses the results of our simulated policy. Since our model comprises multiple complementary decisions (time allocation, travel mode choice, and destination choice), we divide our discussion into two separate parts. We start with the effects of the policy on destination and travel mode choice, and then discuss the time allocation simulation.

5.2.1. *Travel mode and destination choice*

This part of the model only considers the effect of changes in urban park land supply on destination and travel mode choice. We calculate the level of accessibility for some representative consumer, in this case the consumer used to calculate our initial accessibility values for urban park land recreation (female, West-European descent, above low income, no young children in household, and trip during the weekend), see for further details Section 4.1 and Appendix B. The right part of Fig. 1 shows the percentage increase in accessibility due to the increase in supply of urban park land. This difference is the expectation of the change in utility.

As expected, the percentage increase in utility is highest for consumers residing in and close to the changed municipalities The average utility change is 1.47 per cent, yet especially municipalities in the Randstad region, in the west of the Netherlands, often have more substantial increases in urban park accessibility. Since surrounding municipalities benefit too, a change in mode choice is not unlikely: consumers of surrounding municipalities may prefer to recreate at the new urban park located at the border of the urban agglomeration rather than in their hometown. Therefore, we have calculated the probability that a consumer chooses an urban agglomeration for urban park recreation in the old and new setting. Table 4 shows these figures, along with some other statistics.

Behavioral changes are modest. G36 cities have become more attractive to consumers residing in and outside G36 cities. Intriguingly, the increase in accessibility leads to a rise in average distance travelled for trips with G36 cities as destination, which is somewhat counterintuitive. We had expected the average travelled distance to decrease because of G36 residents now choosing their own city as destination, rather than another town. This may have happened in some cases, but the effect of consumers living outside G36 cities now visiting an urban park inside a G36 city is stronger, leading to an increase of the average travelled distance. Non-G36 urban parks are less frequently visited by G36 residents, which explains the lower average travelled distance for urban parks in non-G36 towns.

5.2.2. *Time allocation simulation*

Appendix C discusses the algorithm to calculate time allocation changes resulting from the supply increase policy, and we consider these changes given baseline preferences. Table 5 presents the average change in time allocated to all of the time-use

[14] The choice for twenty per cent is not random. Berkers et al. (2009) consider the average shortage in opportunities for nature-based outdoor recreation around large cities in the Netherlands to be approximately twenty per cent.

categories. Two versions are presented here: one which summarizes the effects on all respondents, and one situation in which only includes respondents with time allocation changes.

The moderate time allocation changes are noteworthy. The share of cases with time allocation changes is less than 3%, mostly (73%) for respondents who had already allocated some time to recreation at urban park land. Time allocation changes are in some cases around forty-five minutes, which is a substantial change. All in all, an increase of urban park land leads to plausible behavioral changes: as extra urban park land reduces the amount of agricultural land, time allocated to urban park recreation and agricultural land recreation respectively increases and decreases. However, the latter effect is smaller than the former, suggesting that some respondents still prefer agricultural environments for recreation despite lower accessibility. The increase in time spent on urban park recreation comes mostly at the cost of the non-outdoor recreation time-use categories: time allocation to both other time-use and other recreation time-use decreases.

Changes in time allocation can also be compared to the characteristics of consumers. The results of our simulation reveal that the average additional time spent on urban park land recreation is the highest on weekends for consumers having to deal with constraints on weekdays: consumers with fulltime jobs. Other responsibilities during weekdays still often prevent consumers from participating in outdoor recreational activities, despite the increase in accessibility.

Less clear is the effect on consumers with other employment situations. Part-time workers and unemployed people appear to change time allocation to urban park land recreation more often on weekdays, and the average absolute change is also higher on weekdays. Thus, some consumer types make use of the new facilities at times at which capacity constraints are less stringent. An increase in park land thus results in higher uses every day, which should be of interest to policy-makers.

The previous subsection has shown that an increase in supply also attracts a new group of users, who live near the new urban park land facilities. The simulation shows that both the average extra amount of time allocated as well as the percentage of users changing time allocation to urban park land recreation is lower for consumers living outside the big cities than for consumers inside these cities, for whom the increase in supply was intended.

6. Conclusion

This paper studies consumer preferences and choice behavior for natural environment types during outdoor recreation trips. Due to extensive urbanization over the years, urban regions in especially the western part of the Netherlands have become more and more spatially connected, diminishing the number of options for consumers to recreate outdoors. The remaining space that can be used for nature-based outdoor recreation should be planned efficiently, and therefore distilling information on consumer preferences is important. Here we discuss the effect of accessibility and personal characteristics for nature-based outdoor recreation in four natural environment types that are distinct in naturalness, openness, and recreational quality.

To understand what drives consumers to choose some natural environment type for recreation, we apply a recently popularized methodology in line with Bhat (2005, 2008). Their Kuhn-Tucker demand system allows for the combination of the discrete choice of participation in an outdoor recreation activity, and the continuous choice of how much time to spend on this particular activity in a unified econometric framework. When the participation decision turns out negative, then the continuous decision obviously also equals zero, and the system resembles a typical discrete choice model when only one time-use category is chosen. We introduce accessibility to the natural environment types through the logsum value estimated in a logit model of travel mode and destination choice, and thus participation and duration decisions are partially explained by the residential location of the consumer.

We do not identify every unique alternative of some natural environment type for destination choice as this would pose too high a burden in the setup of the choice set. In line with other recreation studies however, we aggregate for each municipality all partial landscape pieces of one type into one alternative, and as such we have at most 458 alternatives in the destination choice set.

Our results show that personal characteristics and accessibility both significantly influence time allocation decisions. We find, for instance, an age effect on time expenditure for the included natural environment types, for which we pose both preferences changing with age and the level of recreational facilities (that remain unobserved here) could be responsible. Especially elderly consumers seem to favor easy accessibility of recreational facilities as their physical condition sometimes requires such standards. With the ageing of society in mind, the use of urban park land for outdoor recreation purposes might increase in the future. Our policy simulation at the least shows that such an increase yields substitution away from non-outdoor recreation time-use categories towards recreation at urban park land.

This paper can be enriched by several extensions. First of all, the logit model which now introduces travel mode and destination choice into the MDCEV model is rather concise. The inclusion of destination attributes is not at a really detailed level, while such a detailed analysis (with wider attention for ecological and cultural-historical qualities of environment types, and specific recreational facilities at distinct locations) would greatly benefit the understanding of consumer choice. This would require highly-detailed qualitative data in case of a diversification per natural environment type, and although we acknowledge gathering such data is a heavy burden, it would definitely enrich our understanding of the effect of policy initiatives on consumer choice.

Likewise, the destination choice set now includes all alternatives for each respondent, which might be inconsistent with the consideration set of the consumer. Numerous applications (such as Haab and Hicks, 1997; Parsons et al., 2000) have chosen to include either a deterministic or behavioral choice set for each respondent. It is interesting to see whether current estimates would be replicated with another type of choice set formation. Also, we intend on specifying the utility function in such a way that satiation is introduced non-linearly (see Van Nostrand et al. (2013)). This would greatly benefit the simulation exercise, as consumers that previously allocated zero time to some time-use category would now reveal allocation times that are consistent with the restriction of sixty minutes as minimum duration of a trip.

Our assumption that destination and mode choice are independent of the time spent on an activity should preferably be relaxed. Due to a relatively strong distance decay effect, destinations that are far from the respondent's residential location are not often chosen, but if they are the required travel time puts a lower bound on the time spent on that activity. In the current version of the model there is no distinction between travel time and time actually spent on the chosen activity. The implications of making such a distinction have been analyzed by McConnell (1992) and Larson and Lew (2005) in a somewhat different context.

The MCDEV approach as adopted in this paper implies that the analysis does not fit easily in the conventional microeconomic framework for analysis recreational choice behavior. The main reason is that the budget constraint is ignored while the time constraint is emphasized. Ideally one would like to take both into account, as was proposed by Becker (1965). However, combining the two constraints into a single one requires assumptions (such as the absence of contractually fixed working hours) that may be unrealistic in the setting of recreational choice behavior, while the simultaneous use of a time and budget constraints complicates the model (see Augustin et al., 2017, and Castro et al., 2012).

A final point that is worthwhile to mention is that the panel data we use in principle offer the possibility to take into account individual effects (either of the random or fixed type). This is a potentially useful extension for future work.

Acknowledgement

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Appendix A. Assumptions on travel distance for non-chosen municipalities

As noted, the database reveals the travelled distance to the municipality of choice for each outdoor recreation trip in a natural environment. For our mode and destination choice models we however require the travel distance that the consumer would face for

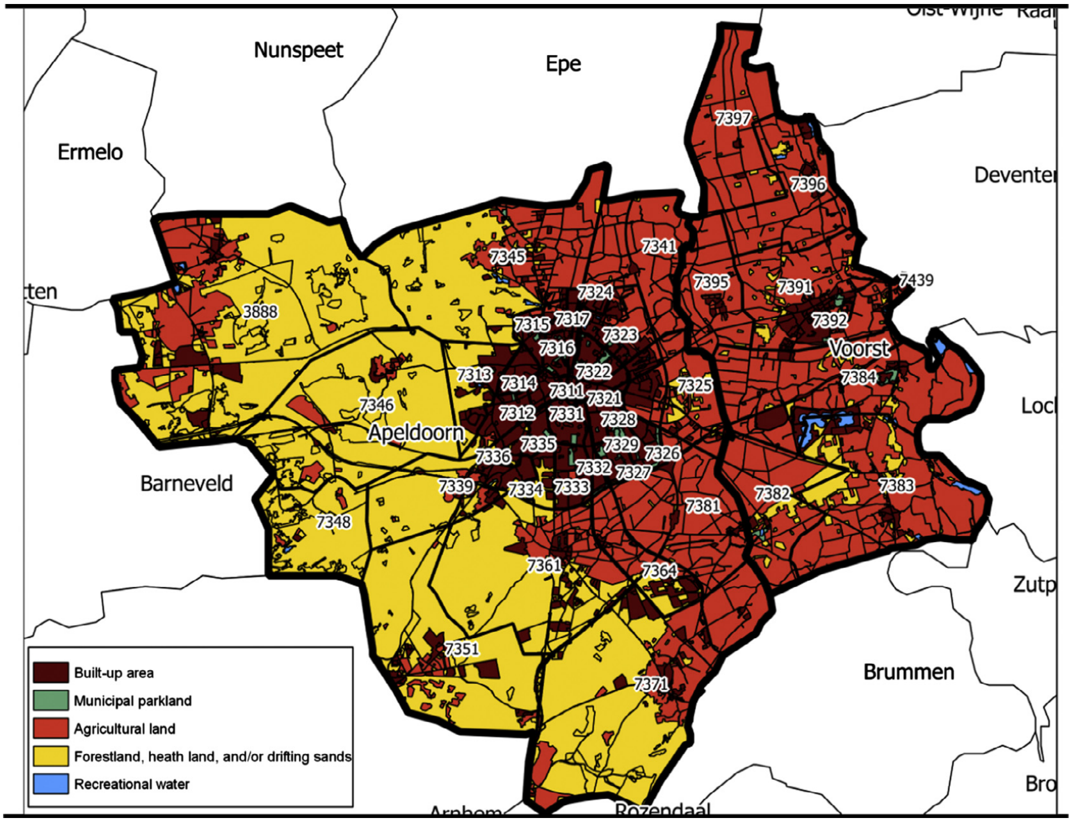

Fig. A1. Land-use in adjacent municipalities Apeldoorn and Voorst.

Table A1
Five highest-supplying postal code areas of “Forestland, heath land, and/or drifting sands”.

Apeldoorn postal code area	Supply (in ha.)	Distance from postal code area 7391 (in km.)
3888	440.35	20.78
7346	294.58	17.07
7371	273.10	15.90
7351	243.26	18.59
7361	205.66	14.54

all municipalities in the respondent choice set. There is however a complication, which is that we do not observe which specific site of a natural environment type the respondent considers in the non-chosen municipalities. To give an example, if a resident of the Hague plans to visit an urban park and chooses Rotterdam as destination, the resident would also have an urban park in Amsterdam in the choice set. It is however unclear whether the Vondelpark or another park is the one considered for Amsterdam. That’s why we need to make some assumptions. These assumptions will be clarified with an example for municipalities Voorst and Apeldoorn (located centrally in the Netherlands), but of course any combination would suffice to present the choices made. Fig. A.1 displays the extent of land use in the municipalities Voorst and Apeldoorn, while the numbers in the figure correspond with four-digit postal code areas.

Imagine a respondent in our database residing in the center of the village Voorst, which corresponds to postal code area 7391. This respondent reveals an outdoor recreation trip at natural environment type “Forestland, heath land, and/or drifting sands” in the municipality Voorst itself. This implies that travelled distance for destination alternative Voorst will take the value that is revealed in the database. For all other alternatives we need to assign some potentially travelled distance, which of course also holds for forest-rich destination alternative Apeldoorn. The assumption we make is that each respondent considers for each municipality the five highest-supplying four-digit postal code areas. It is clear that in the case of destination alternative Apeldoorn the majority of options to recreate in natural environment type “Forestland, heath land, and/or drifting sands” lies to the west of central agglomeration Apeldoorn. The calculation of natural environment type size per four-digit postal code area (the smallest level we can observe) involves aggregation of all unique elements of some natural environment type inside the postal code area. After aggregation, we observe that supply is highest in postal code areas 3888, 7346, 7371, 7351, and 7361. We compute Euclidian travel distance with respect to these alternatives with the help of data provided by geo-information specialist Geodan. Table A1 provides some statistics for these four-digit postal code areas.

We assume that of this set of five postal code areas the respondent chooses the closest option as destination. This implies that distance required to travel for destination alternative Apeldoorn in the case of time use category “Forestland, heath land, and/or drifting sands recreation” equals 14.54 km, which is the distance towards postal code area 7361. Although the amount of forestland in this postal code area certainly does not surpass the amount in for example postal code area 3888, it seems plausible to consider this alternative as the one considered in the choice set, as the burden to arrive at the site is lower for the respondent, and frequently the respondent has to cross the postal code area to arrive at another alternative.

Appendix B. Accessibility heat maps travel mode-destination choice stage

The coefficients of the destination-travel mode choice model can be translated graphically. We have calculated the logsum for some representative consumer, which is here a consumer that is female, of western ancestry, has no young children in the household, has a household income not belonging to the lowest twenty percent, and recreates outdoors on Saturday or Sunday. We assume for each municipality that the consumer resides in the postal code area which also hosts city hall. On top we have projected all patches of the natural environment type, and in both cases we see that our logsum estimates tend to go along well with the supply of the natural environment types.

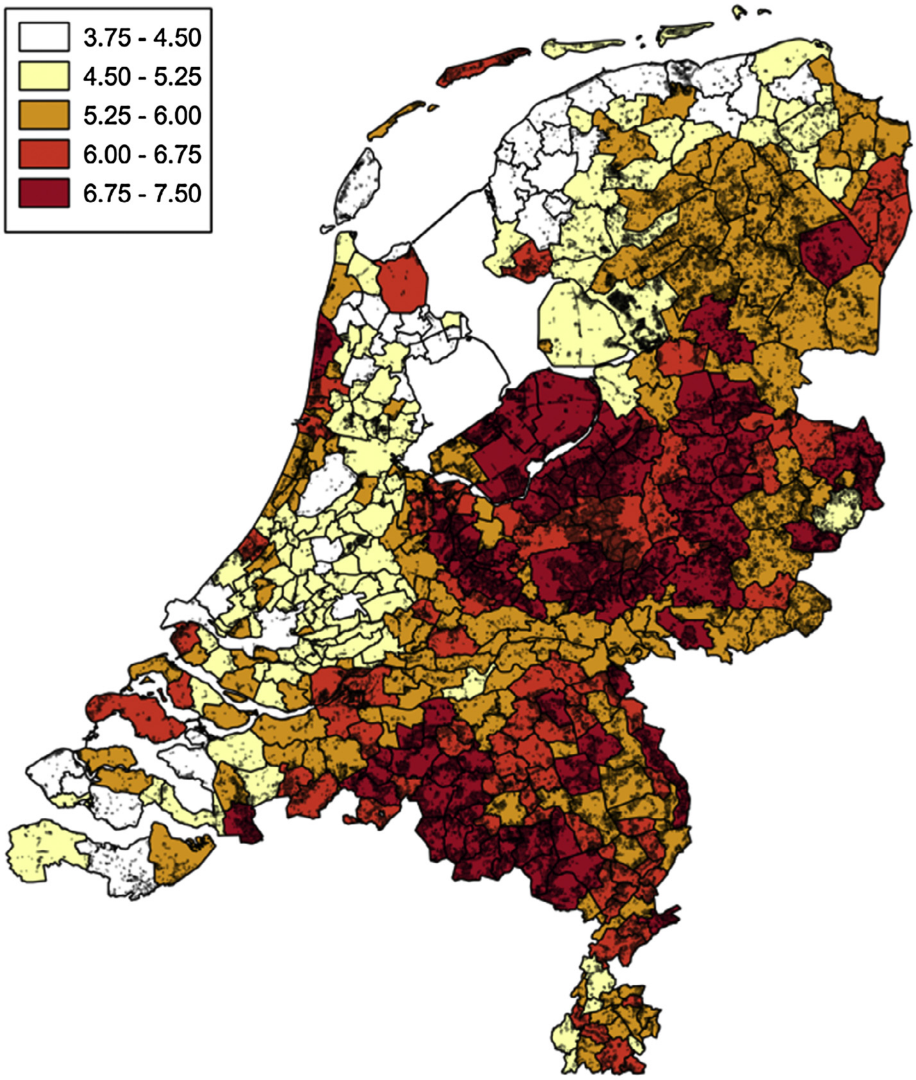

Fig. B1. Accessibility to "Forestland, heath land, and drifting sands".

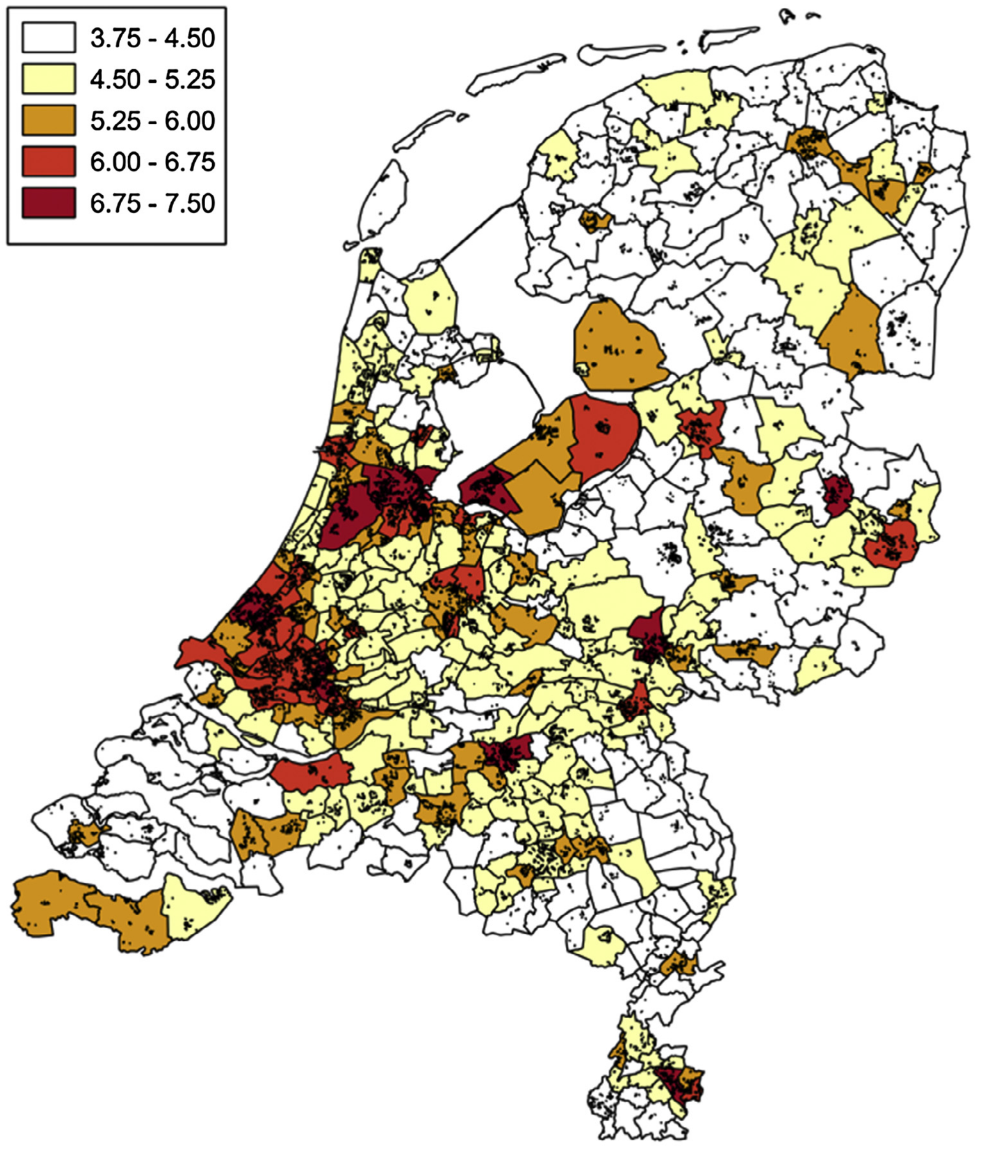

Fig. B2. Accessibility to "Urban park land".

Appendix C. Simulation algorithm for time-use policy evaluation

Policy simulation for consumer demand systems, whether focusing on the allocation of time or income, is quite an undertaking. Applications of the KT demand system typically adopt a constrained non-linear optimization procedure, such as in Von Haefen et al. (2004). This technique differs to traditional approaches for welfare measurement (or general policy simulation) in random utility models (see *e.g.*, Small and Rosen, 1981), as such simulation exercises use information on the stochastic terms from the revealed, initial consumer allocations (what we refer to as baseline case) to simulate the change in time allocation due to some policy initiative.

We apply a simple and flexible iterative technique that shares similarities with Von Haefen et al. (2004). For this algorithm, we make use of the Kuhn-Tucker first-order conditions. One of its essential characteristics is that the KT first-order condition for any interior time-use category with positive consumption equals the *numéraire*-commodity KT condition at optimal allocation:

$$e^{\beta_z q_z + \rho_z G_z^* + \varphi_z}\left(\frac{x_z}{\gamma_z}+1\right)^{\alpha_z - 1} = e^{\varphi_1}{x_1}^{\alpha_1} \text{if} x_z > 0 \tag{C.1}$$

At this point, the consumer is not willing to change the allocation of time (or, equivalently, income) anymore. Given the estimated values of the coefficients and the known values of the explanatory variables, the first-order conditions reveal the values of the differences $\varphi_z - \varphi_1$ for all activities chosen by the consumer on a particular day. For the activities that have not been chosen, we have:

$$e^{\beta_z q_z + \rho_z G_z^* + \varphi_z}\left(\frac{x_z}{\gamma_z}+1\right)^{\alpha_z - 1} < e^{\varphi_1} x_1^{\alpha_1} \tag{C.2}$$

and this reveals $\varphi_z - \varphi_1 < C$, where the value of $C = x_1^{\alpha_1} - e^{\beta_z q_z + \rho_z G_z^*}\left(\frac{x_z}{\gamma_z}+1\right)^{\alpha_z - 1}$. Since we cannot infer the exact value of $\varphi_z - \varphi_1$, we take a number of random draws from its (known) distribution, just as Pinjari and Bhat (2011). For each draw, we make the following computations:

1. In the initial situation the numéraire commodity takes up all time budget (thus, $x_1 = 1440$ and $x_k = 0\ \forall\ k$).
2. Calculate the marginal utility of each time-use category using the estimates of the Kuhn-Tucker demand system.
3. Determine whether the given allocation of time satisfies the condition of optimality for each time-use category. If so, budget allocation is optimal, and the algorithm stops. If not, resume with step 4.
4. Assign a small fraction of budget (*e.g.*, one minute) to the time-use category with the highest value of baseline marginal utility, and equally deduct this fraction from budget spent on the *numéraire* time-use category. Ensure that total allocated budget over all commodities equals total daily minutes, thus 1440. Go back to step 2, and iterate until a desired level of accuracy is reached.

This set of calculated and simulated stochastic terms replicate revealed time allocations in the database perfectly. The effect of some policy initiative is subsequently easy to establish. We take this set of simulated and calculated stochastic terms from the baseline case, recalculate baseline marginal utility for each time-use category with the change in logsum due to the policy initiative, and let the algorithm determine the new optimal time allocation. Matrix and vector notation in matrix programming language enable efficient computation of this algorithm in *GAUSS 12.0*.

Appendix D. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2018.06.024.

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